UPPER LIMB MOTION RECOGNITION BASED ON ELECTROMYOGRAPHY SIGNALS AND SUPPORT VECTOR MACHINE

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Abstract - The increasing requirements of the society to help physically disabilities, the old and the injured individuals to avoid many difficulties to do their day-to-day activities and increase their living condition. The upper limb forearm rehabilitative device has been expected to have a better solution for them. Because the traditional recovery system takes much time to get recovery. In this research, Surface electromyography (sEMG) signals were used as the intention command to movement identification of the upper limb forearm. Six types of major wrist movements collected by placing electrodes on four appointed muscles. Feature extraction was conducted under the Time Domain (TD) Statistical features. Mean Absolute Value (MAV) concluded to be the best feature extraction method for the classification, and it has higher accuracy and the low computational power than other statistical features in order to operate as real-time. The Support Vector Machines (SVM) is designed to conduct classifications task and the model was trained by using a linear classifier. The model operated as a real-time working device and trained the model using 128 features of 128ms. The prediction speed of the model was ~330 obj/sec. The whole process of the model was taken only 131.030ms. The study has obtained zero error rates via the confusion matrix.

Keywords: sEMG; Time Domain; Support Vector Machine; Upper limb

I. INTRODUCTION

The fast-growing science and technology play a significant role in the current society. A diverse range of technologies are launched to the world every day with the more and more new developed features. Humanoid robotics interfaces have always been a very interesting topic in the field of science and technology [1]. The signals which are the human body muscle generate known as the Myoelectric signals (MES). Myoelectric signals contain rich information [2] from which can detect user's intention in the form of a muscular contraction, using surface electrodes [3]. It is clear that amputees or disabled people can generate repeatedly, but gradually varying, myoelectric signal patterns during different levels of static muscle contraction or dynamic limb motion. These patterns used in a control system, known as a myoelectric control system (MCS), to control rehabilitation devices or assistive robots.

A large number of upper limb loss amputees seen in the world due to various accidents, sports injuries. The humanoid assistive robotic hands in the market could provide limited amputees. The reason of that, the most humanoid assistive robotic hands can adopt only for the ones who could give a command with a joystick or a keyboard. These types of hand control robotics are the most popular devices in the world of robotics. Such cases like this, hand free humanoid assistive robotic hands become more and more important.

The study intends to acquire the myoelectric signals of the hand muscles by using surface electrodes through a signal acquisition device. Then the filtered raw data should classify to move properly under the user's intention. The feature extraction is essential to improve the performance of the classifier, and for feature extractions, there can find three main feature in different Domains. Time Domain, Frequency Domain and Time-Frequency Domain [3-5]. The study intended to research the Time Domain. Many researchers have mentioned that the Time Domain contains the better interpretation for the EMG signal analysis.

When it comes to the feature extractions, there are many statistical features were based on the Time Domain. Such as mean absolute value (MAV), Variance (VAR), Standard Deviation (STD) Root Mean Square (RMS) and etc. [1, 2, 4]. Among the all these, this study intended to find the best accuracy statistical feature to apply for the prosthetic device. Moreover as a classifier, support vector machine (SVM) is commonly utilized [6-8].

II. EXPERIMENTAL PROTOCOL

First of all it is important to identify the wrist movements which are used further in this research.

A. Myoelectric Signals

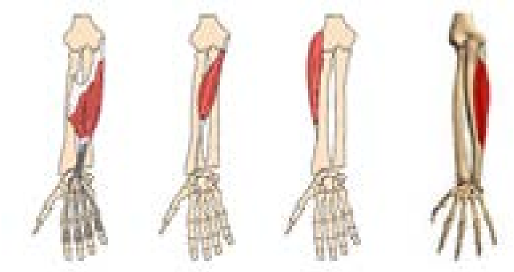
Myoelectric signals are contain abundant information about the intention of a particular individual and also called a motor action potential, is an electrical impulse that produces contraction of muscle fibers in the body. The skeletal muscles that control voluntary movements. The signals have frequencies ranging from a few hertz to about 300 Hz, and voltages ranging from approximately 10 microvolts to 1 millivolt [9]. Myoelectric signals are the Electrical manifestation of the neuromuscular activation associated with a contracting muscle and formed by physiological variations in the state of muscle fiber membranes.

EMG is an Electrodiagnostic technique to measure muscle responses or electrical activities which are produced by the skeletal muscle [7]. The techniques can record and analyze myoelectric signals. Myoelectric Signals also knew as the EMG signals ones captured from the Muscles using the Electromyography.

B. Forearm Muscles

There are five muscle which helped the forearm to move the wrist, hand, and fingers. These muscles are Flexor carpi radialis, Palmaris longis, Flexor carpi ulnaris, Flexor digitorum superficialis and Extensor carpi radials longus. However, the Palmaris longis muscles are not always present. It is a small tendon in between the flexor carpi radialis and the flexor carpi ulnaris (Fig 7). Doctors have discovered that this muscle is absent in about 14 percent of the population.

So considering all these factors, there are four essential muscles which are very important for acquiring EMG signals.



C. Wrist Movements

This study utilized six basic wrist movements for recognition of Biosignals. Six wrist movements used for this study and movements types are respectively, flexion, extension, radial deviation, ulnar deviation, normal and close. It is exactly as per the images below (Fig 1 - 6).

Fig 1. Flexion

Fig 2. Extension

Fig 3. Radial deviation

Fig 4. Ulnar deviation

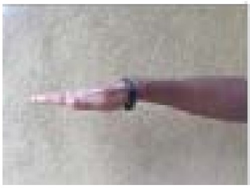


Fig 5. Normal

Fig 6. Close

D. Appling Electrodes to Muscles

The (Table 1) describes how electrodes associated with each muscles in upper limb.

Table 1. Applied electrodes

Hand muscles	Electrodes (Channels)
Flexor carpi ulnaris	1
Flexor digitorum superficialis	2
Flexor carpi radialis	3
Extensor carpi radialis longus	4

E. Data Segmentation

The study collected data from 20 people for the six wrist movements. Each data record was 512ms in duration (512 points for each channel), resulting a 512x4 matrix of segmented signals. For each type of action picked up 60 sets of data, which 30 groups were for the training datasets, and other 30 groups were for the testing datasets. These datasets are also known as trails. Moreover, the data inside the trails are called features.

III. FEATURE EXTRACTION

A. EMG Features

If these raw signals send directly for the EMG classification, the accuracy of the signals may decrease. Therefore extracting features of the EMG signals have been essential. Various types of EMG features were used to improve the performance of the classifier. Proceeding with Time Domain [4] is better since it's easier and it does not take more time like Fourier transform.

B. Time Domain Features

1) Time Domain: Extracting features of the Time Domain is usually quick and easy compared to the other two domains. Since these features were calculated based on the raw EMG time series, Time Domain do not need any other transformations [10]. Time Domain features extracted under many statistical features. Such as STD, MAV, RMS, and VAR. Extracted features mention in all below via diagram (Fig 8 - 11).

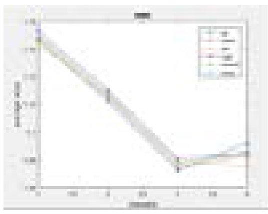


Fig 7. RMS

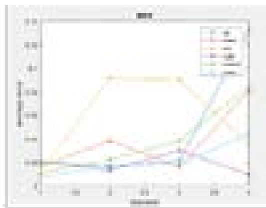


Fig 8. MAV

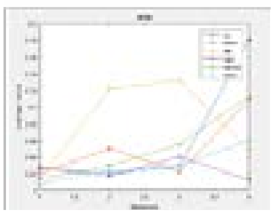


Fig 9. STD

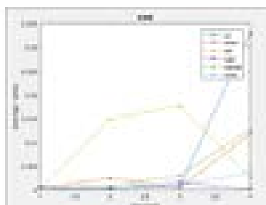


Fig 10. VAR

Different motion result gives different muscles the information about different channel that should be distinct, and it returns each channel ought to express particular character in muscles.

In order to get quick results, it is better to test extract features by reducing time frame. At the beginning, extracted features from 512 feature of 512ms. The testing was done using 256 features of 256ms and 128 features of 128ms.

The next step was data classification utilizing extracted features. In order to create a model machine learning, and MATLAB used for this study.

IV. DATA CLASSIFICATION

Data classification is the process of organizing data into categories for its most effective and efficient use. A well-planned data classification system makes essential data easy to find and retrieve.

Classification learner is an application on the MATLAB machine learning toolbox. It has the capability of training models to classify data. Utilizing the application can explore supervised machine learning. The app can explore the data, select features, specify validation schemes, train models, and assess results.

A. Support Vector Machine (SVM) for Classifications

The support vector machine is a classification method which is widely used for data analyzing and pattern recognition [8]. The SVM helped to create hyperplane between two or more data sets to recognize the class. SVM is base on the concept of decision planes that define decision boundaries and use supervised learning model, which has capability of analyzing large data sets in order to recognize a pattern. Classification is always done based upon the training and test datasets. The classifier separates two or more data sets into respective groups with a line known as a linear classifier. However, most of the classification tasks are not that simple to separate with a line.

B. K-Fold Cross Validation

K-Fold Cross Validation is the widely used cross-validation type in machine learning. The machine itself will partition the original given training data set into k equal sub-sets. Each Subset was called a fold. The value of the k takes any value as per the user's necessity. This research used 5 folds cross-validation. There were 5 subsets, and each subset included 20% of the full data, and 5 experiments conducted.

V. EXPERIMENTAL RESULTS

The four signals are acting differently for the same wrist movement. For example, the (Fig 12) shows wavelets of all four signals on the extension. The maximum amplitude for the specific movement is available in channel 4.

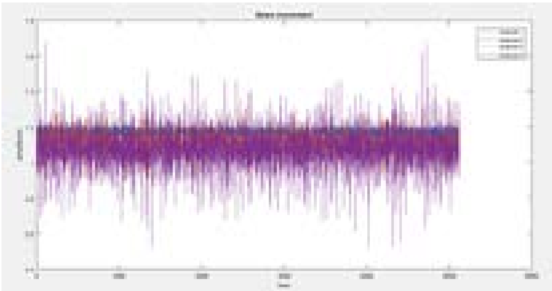


Fig 12. Extension signal

The below figures belongs to the flexion. As in the (Fig 13), the channel 4 has maximum amplitude in flexion. Therefore can get the result that the 4th channel gives precious information about the flexion.

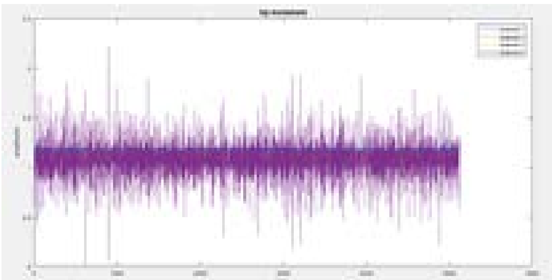


Fig 13. Flexion signal

The below figures belongs to the Radial deviation. As in the (Fig 14), the channel 2 has maximum amplitude in Radial deviation. Therefore can get the result that the 2nd channel gives precious information about the Radial deviation.

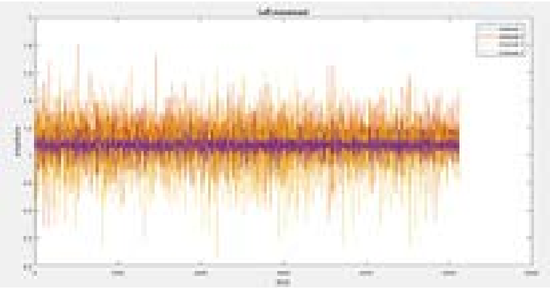


Fig 14. Radial deviation signal

The below figures belongs to the ulnar deviation. As in the (Fig 15), the channel 3 has maximum amplitude in ulnar deviation. Therefore can get the result that the 3rd channel gives precious information about the ulnar deviation.

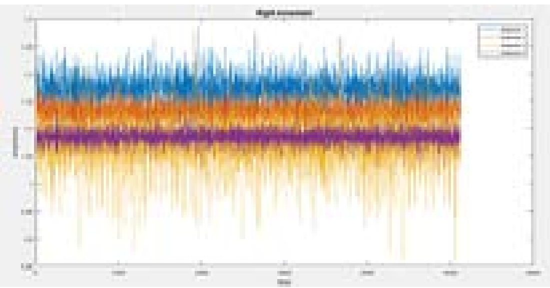


Fig 15. Ulnar deviation signal

The below figures belongs to the normal movement. As in the (Fig 16), the channel 4 has maximum amplitude in normal movement. Therefore can get the result that the 4th channel gives precious information about the normal wrist movement.

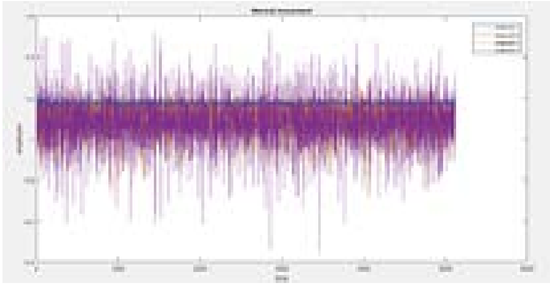


Fig 16. Normal movement signal

The below figures belongs to the close movement. As in the (Fig 17), the channel 4 has maximum amplitude in close movement. Therefore can get the result that the 4th channel gives precious information about the close wrist movement.

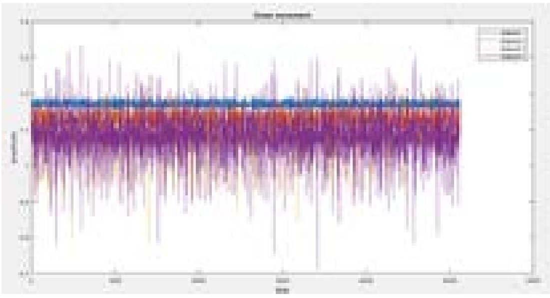


Fig 17. Close movement signal

For each wrist movement, there is a specific channel which has maximum amplitude. That means each four channels provide abundant information for the specific wrist movements. The below table (Table 2) contain the average values of four different Time Domain statistical features in four channels and the variation for six wrist movements.

Table 2. Average values

	Channels	STD	VAR	RMS	MAV
Flexion	1	0.02648	0.00070	1.16538	0.02008
	2	0.02064	0.00043	1.12223	0.01590
	3	0.02816	0.00079	1.07224	0.02095
	4	0.18050	0.03282	1.09181	0.13249
extension	1	0.02014	0.00040	1.16738	0.01592
	2	0.05013	0.00251	1.12493	0.0382
	3	0.02219	0.00049	1.07431	0.01577
	4	0.10839	0.01179	1.08297	0.08042
Radial de.	1	0.01347	0.00018	1.16312	0.01062
	2	0.12127	0.01477	1.12716	0.09152
	3	0.13203	0.01769	1.07915	0.08987
	4	0.04859	0.00238	1.07539	0.03487
Ulnar de.	1	0.02721	0.00074	1.17270	0.02069
	2	0.01694	0.00028	1.13028	0.01319
	3	0.04029	0.00162	1.08082	0.02991
	4	0.01230	0.00015	1.08466	0.00953
Normal	1	0.01409	0.00020	1.16865	0.01096
	2	0.02938	0.00086	1.12605	0.02178
	3	0.05517	0.00305	1.07693	0.03814
	4	0.11249	0.01269	1.08551	0.08393
Close	1	0.00843	7.12E-0	1.17041	0.00681
	2	0.02297	0.00052	1.12819	0.01751
	3	0.02944	0.00092	1.07795	0.01726
	4	0.06035	0.00365	1.08384	0.04456

Data were used to scatter plots diagrams of wrist movements according to each feature extraction type. Feature extractions were done in Time Domain in this study. The statistical feature extractions were graphed using scatter plots of six specific wrist movements are as follows (Fig 18 - 21).

Fig 18. STD Plot

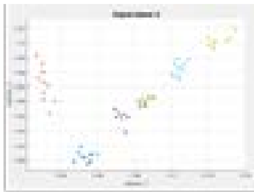


Fig 19. RMS Plot

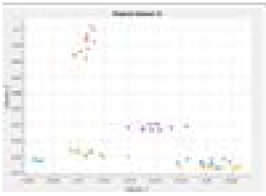


Fig 20. MAV Plot

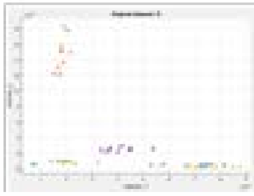


Fig 21. VAR Plot

In order to acquire signals with more speed accuracy was tested again by reducing features and time (Table 3).

Table 3. Accuracy testing by reducing the time

No. of Features and milliseconds	STD	MAV	RMS	VAR
512	100%	100%	100%	100%
256	100%	100%	100%	100%
128	100%	100%	100%	100%

Since the specific research under the supervised learning, the research has shown the accuracy of the model using this confusion matrix. The specific confusion matrix is shown below (Fig 22).

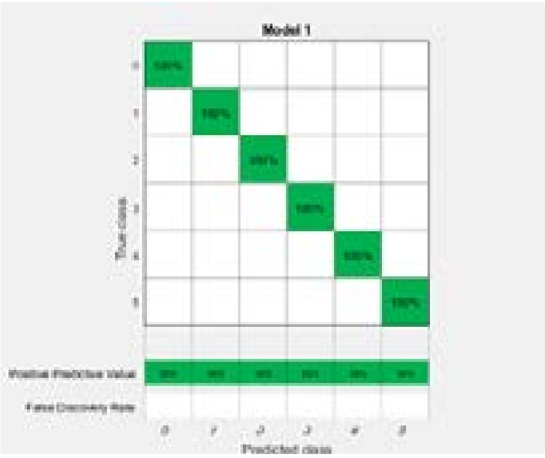


Fig 22. Confusion matrix of the developed model

As in the above (Fig 22), true classes 0 to 5 represent the actual wrist movements and in the predicted classes represent the predicted wrist movements. According to this confusion matrix the accuracy of the model is 100% and there are no errors at all. Therefore the model is running at 0 error rate.

VI. CONCLUSION

The study has successfully developed a wrist movement recognition system using Biosignals. All the experiments and tests obtained the intended accuracy of 100%. Six different wrist movement (extension, flexion, radial deviation, ulnar deviation, normal and close) studied under EMG signals of four different channels. Performance of each channel according to the specific wrist movement is clearly shown by the result.

To do classification is essential to extract the features. Feature extractions on the Time Domain and the algorithms used as STD, RMS, MAV and the VAR. From all these statistical features, MAV demonstrates as the best feature for the classification. Since its' higher accuracy and the low computational power in order to operate as real time.

Classifications explored through SVM experimentation. SVM was the most suitable application for data classification in this research. The model trained under the linear classifier since it is the most primary classification process. Finally, the results have shown that the all testing dataset were obtained 100% of accuracy with 100% of motion identification.

However, for a real-time working system, the time duration for the whole process should be within 300ms. When it comes to the model which was developed, it takes EMG signals of 128 mili-seconds specific to the wrist movement. Moreover, the speed of the model to identify the specific wrist movement is ~330 obj/sec.

Since it takes only 131.030ms for whole process of the model, which was developed and the specific model can apply to a real-time working system successfully.

The current model was developed by using SVM. For the future works, to develop the existing model by using the Hidden Markup Model (HMM) with SVM and model works as a hybrid model. Using hybrid model expect to get high accuracy for the very small movements of the upper limb.

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